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PRELIMINARY DRAFT
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Preventative health care is often cited as one solution to the growing share of health care spending in the U.S. GDP. One significant barrier to patient adoption of preventative regimens is the fact that they generally require a person to forego consumption and activities that they enjoy today for the promise of some future payoff. The degree to which a person prefers the present relative to the future will therefore be an important determinant in the decision calculus with respect to the demand for preventative medicine. We address this question by analyzing data collected in a nation-wide survey of adults over the age of 40. We estimate two multiple-bounded dichotomous choice models using maximum likelihood. The first predicts the latent discount rate for each individual and the second predicts the latent willingness to pay for cancer screening as a function of the individual discount rate. The results suggest that the average respondent in the survey has an underlying discount rate of 36.8% per year, and is willing to pay around $280 out of pocket for the hypothetical cancer screening. Higher rates of discount significantly reduce WTP.

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Estimating the Effect of Individual Time Preferences on the Demand for Preventative Health Care

Time preferences are considered a fundamental characteristic of economic behavior. Standard utility theory, set in a dynamic model, has strong predictions about the effect of different rates of discounting on an individual's behavior. However, there is very little empirical evidence that tests these predictions at the individual agent level. In general, we expect that higher rates of discounting for an individual will lead them to more strongly shift consumption of economic goods to the present, relative to a person with lower rates of time preference. Consequently, patients who discount the future more heavily should be much less likely to demand preventative health care than patients with low rates of time discounting. This is because prevention requires patients to engage in activities they often do not enjoy today (for example, reducing the intake of high-fat and high-sodium foods, exercising, losing weight, consuming pharmaceutical products, etc.) in order to prevent adverse outcomes in the future. However, despite the potential importance of this time discounting effect on the demand for preventative medicine, it has not been studied to date.

We investigate the direct impact of higher discount rates for an individual patient on her demand for a hypothetical cancer screening technology using a compensating variations method, using a nationally-representative survey of 2000 individuals over age 40. In addition to a set of standard demographic and economic questions, respondents' willingness to pay (out of pocket) for cancer screening and willingness to accept interest rate payouts were assessed using a two-step elicitation method. Following a brief description of the cancer screening technology and its potential benefits, respondents were asked whether they would be willing to pay a specific amount of money out of pocket to get the test. The offer amount was randomized for each respondent. If the response was "yes", the question was repeated with a second (randomly assigned) higher price. If the response was "no," the question was repeated with a second (randomly assigned) lower price. Similarly, individual rates of time preference were elicited by asking respondents to imagine they had won a lottery that will pay them $10,000 one year from that day, or some higher value 6 years from today. (Respondents were also told the interest rate that a savings account would pay in order to generate the offered higher future payment.) If the individual agreed that they would accept the future payment, then the question was repeated with a lower future value, and commensurately lower interest rate. If the respondent preferred the earlier payment, the question was repeated with a higher future payment and interest rate. Again, all payments (and so, interest rates) were randomly assigned to each respondent.

With the data in hand, we estimate a two-stage model, where the first stage implements a one and one-half bounded dichotomous choice model to predict a latent discount rate. These latent rates are then predicted for each person, and used as an explanatory variable in a double-bounded dichotomous choice model of willingness to pay (WTP) for cancer screening. We find that respondents have a discount rate of approximately 38% per year, on average, and that this discount rate is negatively related to the willingness to pay for cancer screening, which is estimated to be approximately $280, out of pocket.

The final results of this model should be of interest to economists in general, as well as health policy makers. For economists, this will be one of the first attempts to integrate an estimate of individual agents' discount rates with their demand for a time-dependant service. Consequently, the results will inform an important, but understudied, intersection between economic theory and empirical estimation. For policy makers, the information gain with respect to the demand for preventative services should be similarly informative. Clinicians are often frustrated by the difficulty in convincing patients to consume preventative health care. This reluctance is typically taken as an indication that patients are poorly informed, and so education programs are proposed as a solution. These results indicate, however, that patients are at least in part making rational decisions based upon their discounting of the future.

The paper proceeds by reviewing the literature on the estimation of individual rates of time preference and on models that predict the demand for preventative health care. Section III presents the details of our one and one-half bounded and double-bounded dichotomous choice models. Section IV presents the results, and Section V concludes with a discussion of the implications of this work and suggestions for future research.

II. Discount Rates and the Demand for Preventative Medicine

Michael Grossman (1972) introduced the concept of health as a component of human capital, which depreciates and in which investments can be made. Since that seminal contribution, a number of economists have investigated many dynamic aspects of health production and health care demand (for example: Wagstaff, 1986; van Doorslaer, 1987; Wagstaff, 1993; Grossman and Kaestner, 1997; and Zweifel and Breyer, 1997). Theoretically, there have been a number of models which have explicitly modeled the role of time preferences on general human capital investments, of which health care is one (schooling investment is the most widely studied dimension). The Becker and Murphy (1988) model of rational addiction is perhaps the most successful of these. In their model, agents have foresight, and make human capital (and other consumption) decisions based upon the current utility and future utility generated. They find that higher rates of time preference tend to lead to lower current consumption of goods, but will increase current consumption of addictive products. As Grossman (2000) notes, the Becker / Murphy model predicts a discount rate effect only under certain circumstances (the result is generally ambiguous in sign, and uncertain in magnitude). Ehrlich and Chuma (1990) explore the general implications of the Grossman (1972) model more completely, and do pay particular attention to the impact of time preference. They find that increasing the rate of discounting the future tends to reduce investments in health capital – though this result holds only on average. The empirical research we present below will test these "average" predictions from the Grossman (1972) and Ehrlich and Chuma (1990) models.

While the theoretical guidance is relatively clear with respect to the impact of time preference in health care demand, direct empirical test of these predictions are notably absent from the literature. A number of authors have tested the effect indirectly, by demonstrating a schooling / health investment relationship is consistent with an inverse relationship between discounting and human capital investment (Farrell and Fuchs, 1982; and Berger and Leigh, 1989). However, these are only indirect tests, and subject to multiple interpretations. Consequently, in the words of Grossman (2000, page 401): "definitive evidence with regard to the time preference hypothesis is still lacking." While *definitive* evidence may be long in coming, we will at least present *direct* evidence in this work.

One reason that direct evidence on the relationship between time preference and health care demand is scarce is the difficulty in measuring time preference. Until fairly recently, the art of estimating individual discount rates has been poorly explored. However, there is currently a strong, and growing, literature on which to draw. (For a summary of this literature, see Frederick, Loewenstein, and O'Donoghue, 2002.) There are three primary methodologies for assessing individual discount rates. The first is to use natural experiments in which individuals must choose between alternative with differential time dimensions, such that a discount rate can be inferred. An example of this literature is Warner and Pleeter (2001), which took advantage of data generated from an early retirement program in the U.S. military to estimate discount rates for enlisted men and officers. A second methodology is to present individuals with hypothetical or real payouts that vary in their time dimension in an experimental setting. Coller and Williams (1999) and Harrison, Lau, and Williams (2002) represent examples of this research. The third methodology employed is to present survey subjects with a set of hypothetical present and future payouts and estimate discount rates using a contingent valuation (CV) method. We will employ this latter approach, both for eliciting discount rates and for eliciting willingness to pay for our potential cancer screening technology.

Physicians have a variety of tools at their disposal to improve health, both current and future. Often, medical care is aimed at changing health behaviors or providing interventions in the present with some hope of reducing the incidence of acute conditions in the future. This type of health care, when no symptoms currently exist, is known as primary prevention. In addition, physicians may screen for diseases which the patient may currently have, though no acute symptoms are present. This type of health care is known as secondary prevention (and is, technically, the sort that our empirical models will evaluate). While clinical tools are well validated, physicians often complain that they cannot convince large numbers of their patients to adopt primary prevention practices. For examples of such discussion in the cardiovascular realm, see reports from the 33rd Bethesda Conference Task Forces #3 (Ades, et al., 2002) and #4 (Okene, et al., 2002) and Giorgianni, Grana, and Keith (2003). In this paper, we will study determinants of demand for screening for lung cancer. As with cardiovascular disease, there is evidence that screening with current CT technology can detect cancers early (Henscheke, et al., 1999). Whether this screening is cost effective is currently controversial, with some findings suggesting not (Mahadevia, et al., 2003), and some suggesting it may soon be cost-effective (Miettinen, 2000). However, the question that remains is whether patients would, in fact, be willing to pay currently out-of-pocket for potential health gains in the future (reduced future mortality associated with early treatment). The question is relevant, since evidence suggests that willingness to pay (willingness to seek) screening for other cancers varies by patient characteristics and financial constraints – for example, mammography for breast cancer has been studied by Tudiver and Fuller-Thomson (1999).

Consequently, consistent with much extant literature, we examine data generated from a national survey, where willingness to pay (WTP) for lung cancer screening, willingness to delay payouts from a hypothetical sweepstakes, and respondent characteristics were collected. We use two multiple-bounded dichotomous choice models (described in detail below) to simultaneously model each respondents' discount rate and WTP for screening. This work will simultaneously add to the literature which seeks to understand individual time preferences and also to the literature which models WTP for non-traded goods. Additionally, we will provide some of the first direct evidence of the impact discounting has on preventative health service demand – and discuss the implications of this evidence for clinicians and policy makers.

III. Methods

a. Survey

We conducted a randomized telephone survey of 2000 adults (over 40 years of age) during the second half of 2002 and the first half of 2003. Random digit dialing was employed. The only inclusion restriction was age. In addition, we over-sampled current and former smokers. After eliminating observations with incorrect survey administration, and observations from Alaska and Hawaii (due to outlier status with regard to costs of living and market interest rate options), we retained a sample of 1904 individuals. Table 1 presents the demographic information on our sample.

Contingent valuation (CV) is a widely used method to assess WTP for goods not traded in the marketplace. While is has often been used to value environmental resources, it has also found a home in health economics in assigning dollar values to many things which are not traded in the market (such as life-years in the future) and services which are traded in the market, but for which patients do not naturally pay the full marginal cost out-of-pocket. The earliest utilized approach was to survey people, asking how much they would be willing to pay for a particular good. Often, however, the survey respondents often have no direct experience with purchasing the service being evaluated. Consequently, answers may be noisy. Additionally, when the survey offered several examples of value the responses may also suffer from framing, in that the value offered by the survey may influence the respondent's actual expressed valuation (see, for example, Diamond and Hausman (1994).)

Many of the problems of this simple survey method can be avoided by using the dichotomous choice approach. In this approach, participants are asked whether or not they would pay a certain amount for the good in question. The amount asked is varied across participants. In this way, the question is not "framed" for respondents – at least they are not asked to consider whether the offered amount corresponds to their maximum willingness to pay. Further, by asking whether they will pay $x, respondents can perceive no signal as to whether "Yes" or "No" is the "preferred" answer that the surveyor desires. Thus, the elicited response can be expected to better represent the choices of the survey participant (see Boardman *et. al* 1996, pages 347-349). This approach is known as the single-bound dichotomous choice model.

Typically, the actual dollar amount offered varies across a small number of values. Less commonly, the value is varied randomly for each respondent (a method that significantly raises the difficulty of administering the survey). However, since there is a potentially large increase in the precision of the estimates by varying offer amounts for each individual, that is the approach we take in this study.

One disadvantage of the single bound dichotomous choice method is that if someone answers “Yes” to the question “Would you be willing to pay $x for the good?”, then the dollar amount can only be seen as a lower bound to their true WTP (or an upper bound, if they answer “No”). An alternative approach which has recently been applied to health economics (Bradford, et al., 2003) takes the elicitation process one step further. This method is known as double-bounded dichotomous choice contingent valuation (DBDC) (Hanemann, 1985; Cameron and James, 1987). When employing the DBDC method, a survey poses follow-up questions to the initial WTP query. If a person responds “Yes” to the WTP question, then they are asked a follow-up question where the dollar amount is raised. If the person responds “No” to the first question, then they are asked the question again, this time with a lower dollar amount.

To illustrate the advantages of DBDC, let P_1 represent the initial dollar amount presented a respondent, P_2 represent the follow-up amount if the person responds “Yes” to the initial question, and P_3 represents the follow-up amount if the person responds “No” to the initial question (where $P_3 < P_1 < P_2$). Thus, if a person answers “Yes – Yes,” we know that P_2 is the lower bound on their WTP, and if the person answers “No – No,” then we know P_3 is the upper bound on their WTP. In this regard, DBDC is similar to the usual single bound contingent valuation method (except that we have come closer to the true WTP by being able to set P_3 or P_2 as the bounds, rather than P_1 – which would be the bound in both cases in the single bound contingent valuation method). However, if a person responds “Yes – No,” then we know that their true willingness to pay lies *between* P_1 and P_3. We have placed both an upper and lower bound on the true WTP. Similarly, for a person who answers “No – Yes,” we know that true WTP is bounded between P_3 and P_1. Thus, the DBDC approach generates more information in each of the four cases – either the upper or lower bounds are defined more precisely or the true WTP is clearly bounded on both sides. This information gain implies that the DBDC approach may be significantly more efficient than the single-bound method (Hanemann, Loomis, and Kanninen, 1991; Kanninen, 1993).

For this research, we asked two sets of DBDC questions. The first was targeted at eliciting the respondent’s implicit discount rate, the second was aimed at eliciting the respondents willingness to pay for a hypothetical new cancer screening tool. The actual questions were as follows. For the discount rate elicitation, we asked:

“I want you to imagine that you have just won a sweepstakes prize. Imagine that you have been offered two choices for how you will take your prize. Which of the following two choices would you select?

A. *In $10,000 cash paid to you one year from now?*
B. *In $xxx cash paid to you six years from today. (This is like having a savings account that pays an interest rate of r_1 % per year.)”*

The dollar amount was randomized for each survey respondent, and the respondents were told the implied interest rate, r_1, which was calculated based upon the randomly assigned dollar amount and a 5 year time frame (since the second prize which is paid in six years is to be compared to the first prize, which is paid in one year). The rationale behind the year-long delay in any reward is to avoid confounding the estimated discount rate if individuals discount the future differently for payouts that are imminent compared to payouts that are further in the future.[1]

If the underlying discount rate for the person lies below the offered rate, r_1, then this means the money will grow faster by delaying the prize than the person's rate of discounting the future – in which case the respondent will choose to delay payment. On the other hand, if the respondent's innate discount rate is above r_1, then they will discount the future more quickly than the prize will grow, and so the person would choose the $10,000 in one year. Consequently, if the respondent chose to take the $10,000 payment in one year, an identical question was asked with a new dollar amount that was higher (by a random factor) than the initial one, corresponding to a higher interest rate, r_2. Contrarily, if the person selected the future payment, a new question with a randomly lower dollar amount and interest rate r_3 was asked. It is important to note that the DBDC questions about time preferences were in terms of willingness to accept. That is, unlike the WTP questions, a person would choose to take the payment in six years if, and only if, her underlying discount rate is below r_1.

Similarly, we asked a set of questions to elicit willingness to pay for a new, high speed / high precision CT scan for lung cancer. Just prior to asking the series of questions, the new technology was briefly described, along with a statement that it is hoped that earlier diagnosis of lung cancer would translate into better treatment outcomes. After the description of the new scanning test, respondents were asked:

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[1] There is a growing literature that suggests that people may in fact discount the distant future less heavily than they discount the proximate future. Most commonly this has been discussed in terms of hyperbolic discounting. For a summary of the measurement and implications of non-constant discounting, including hyperbolic discounting, see Frederick, Loewenstein, and O'Donoghue (2003).

"Would you be willing to pay $\$P_1$ out of your pocket to have this scan?

A. Yes

B. No"

As with the discounting questions, the dollar amount was randomized for each respondent.

If the respondent's underlying WTP is *above* the offer price of $\$P_1$, then the person would answer "Yes" to the question – at which point they would be asked the question a second time, with a higher offer price of $\$P_2$. (Note, that this is the opposite of what happens with the discounting questions, where the respondent accepts the offered rate only if her personal discount rate is below r_1.) Alternatively, if the respondent's WTP lies below $\$P_1$, then she would answer "No" to the question, and have a follow-up question which offers a lower offer price of $\$P_3$. Again, the second offer prices, $\$P_2$ and $\$P_3$, were randomly assigned for each person (where the difference between $\$P_1$ was a random positive or negative number – depending on the answer to the first question). With the discounting and WTP responses in hand, we proceed to the specification and estimation of the individual models.

b. Discounting Model

b.1 – Maximum Likelihood Estimator

Estimating individual preferences with regard to time is a relatively recent line of inquiry in applied and experimental economics. However, even in the brief time that economists have been studying this issue, they have uncovered a number of anomalies – results which violate the standard assumption in a number of dimensions. This list includes the findings that many individuals seem to:

- discount the near future more heavily than the distant future (often expressed as hyperbolic discounting)
- discount smaller outcomes more heavily than larger
- discount outcomes which cluster rewards more heavily than outcomes of equal value that spread rewards across time
- discount series of constant, or decreasing, outcomes more heavily than improving sequences
- discount gains more heavily than losses

The latter two anomalies are of particular interest here. Our questions in essence presented respondents with one offered rate, r_1, and then either improved the offer (if r_1 was too low) or reduced the offer (if r_1 was acceptable). In essence then, the first question was about a possible discount factor in isolation, and the second question became – by default – a question in a series. In attempting to implement the double-bounded dichotomous choice model (which follows both arms – improving and depreciating), we discovered that respondents reacted differentially to the two possible arms. In particular, a single-bounded model using the first question (regarding r_1) performed well, as did a single-bounded model using the information only from the improving arm (regarding r_2). However, a single-bounded model for the depreciating arm (involving r_3) performed very poorly – such that no predictor was statistically significant and the pseudo-R^2 was extremely small. Additionally, feasible values did not exist for any DBDC model that incorporated the depreciating arm of the series.[2] Consequently, we will implement a One and One-Half Bounded Dichotomous Choice (HBDC) model for the discount rate estimator.[3]

We assume there is some underlying individual discount rate, which is represented as a latent variable R^*. Let

$$R_i^* = X_i\theta + \varepsilon_i$$

where $\varepsilon_i \sim N(0, 1)$. In addition, we impose the restriction that $R_i^* \in \Re^+$ - that is, non-positive discount rates are not permissible. Note that, for the first question, the probability that the responded will choose the distant value is equal to:

$$\begin{aligned} \Pr[\text{Future Value}] \equiv \Pr[\ F\ ] &= \Pr[0< X_i\theta + \varepsilon_i < r_1] \\ &= \Pr[- X_i\theta < \varepsilon < r_1 - X_i\theta] \end{aligned}$$

thus,

$$\textbf{[Eq. 1]} \qquad \Pr[F] = \Phi(r_1 - X_i\theta) - \Phi(- X_i\theta)$$

In Figure 1, this corresponds to the case when ε falls into region I. Note, unlike the DBDC model, we only estimate one arm for those who choose the (six years in the) future payout – since they were offered a lower rate in the second question, which generated the anomaly noted above.

For those who choose the present option (payoff in one year), there are two possible scenarios. First, they may have chosen the present option for the first question, and upon being offered a higher rate, r_2, in the second question choose the future payment.

[2] Details regarding the exploration of the anomalies associated with the depreciating arm of the responses are available from the corresponding author.

[3] This difference in behavior across the improving and depreciating arms did not appear for the WTP questions, so that a full DBDC model will be utilized for that.

We will designate this outcome as "P-F." Note, that in this circumstance, we know that the underlying discount rate must lie between r_1 and r_2. Thus,

$$Pr[P\text{-}F] = Pr[\ r_1 < X_i\theta + \varepsilon_i < r_2\ ]$$

$$= Pr[r_1 – X_i\theta < \varepsilon_i < r_2 – X_i\theta]$$

and thus,

[Eq. 2] $$Pr[P\text{-}F] = \Phi(r_2 – X_i\theta) - \Phi(\ r_1 – X_i\theta)$$

This corresponds to the case where ε falls into Region II in Figure 1.

Finally, the last possible case in the discounting model is the scenario where the respondent chooses the present payoff in the first and second questions, designated "P-P." In this case, we know that the discount rate is above r_2. Thus,

$$Pr[P\text{-}P] = Pr[\ X_i\theta + \varepsilon_i > r_2\ ]$$

$$= Pr[\varepsilon < X_i\theta - r_2\ ]$$

and thus,

[Eq. 3] $$Pr[P\text{-}P] = \Phi(\ X_i\theta - r_2)$$

This corresponds to the case where ε falls into Region III in Figure 1.

If we define dummy variables, d^F, d^{PF} and d^{PP} to indicate when each of the respective outcomes obtain, then the log likelihood function becomes:

[Eq. 4] $$\ln L = d^F * \ln\{\Phi(r_1 – X_i\theta) - \Phi(\ - X_i\theta)\} + d^{PF}*\ln\{\Phi(r_2 – X_i\theta) - \Phi(\ r_1 – X_i\theta)\} + d^{PP}*\ln\{\Phi(\ X_i\theta - r_2)\}$$

which can be maximized using standard maximum likelihood packages (in our case, Stata) across θ. In actual implementation, the maximum likelihood estimator requires parameters on the offer rates (which are effectively identical). Consequently, the true parameters of interest are $\hat{\theta} = \frac{\hat{\theta}_1}{\hat{\alpha}}$, where $\hat{\theta}_1$ are the parameters on X generated by the maximum likelihood estimator, and $\hat{\alpha}$ is the average parameter on the offer rates. We report $\hat{\theta}$ in the tables below. Once we have recovered the normalized parameter vector $\hat{\theta}$, then we can estimate a discount rate for each individual, *i*, in the data, $\hat{R}_i^* = X_i\hat{\theta}$.

b.2 – Explanatory Variables:

We include explanatory variables that fall into several classes. These are:

- *characteristics of the individual that are expected to influence general preferences* – respondent age (*age*), respondent gender (*male*=1 if respondent is male), race (*black*=1 if respondent is African American; *otherrace*=1 if respondent is not Caucasian or African-American; Caucasian is the excluded category), marital status (married=1 if respondent is married), and educational attainment (*hschool*=1 if respondent graduated from high school; *somecoll*=1 if the respondent attended some college; college graduate is the excluded category).
- *characteristics that reveal underlying preferences with respect to risk* – self-reported health status (*goodhealth*=1 if respondent reported she was in good or excellent health), self-reported cancer risk (*selfcnrisk*=1 if respondent reported that she believed herself to have a high or very high risk of cancer), and smoking status (*formersmoker*=1 if the respondent has smoked in past, but not in present).

- *characteristics that affect the opportunity costs of medical care* – insurance status (*medicare*=1 if respondent is covered by Medicare; *medicaid*=1 if respondent is covered by Medicaid; *selfins*=1 if the respondent has private, non-group insurance; *hmo*=1 if the respondent has HMO coverage; *otherins*=1 if the respondent has some other form of insurance; non-insured is the excluded category), employment status (*employed*=1 if respondent is currently employed; *retired*=1 if respondent is currently retired; non-employed is the excluded category), and income (six discrete income level indicators, *inc1 – inc6*, plus *unknowninc*=1 when the respondent refused to answer the income question; income over $100,000 per year is the excluded category).

The variables listed above are expected to impact both the demand for medical care, and the returns to health investments. Additionally, we include variables that are expected to impact only the discount rate. These include a year indicator (*year03*) and a set of census region indicators (*newengl*, *southeast*, *Midwest*, *plains*, *west*; Mid-Atlantic is the excluded region). These variables are expected to be associated with variations in the interest rates being offered on savings accounts / certificates of deposit by local banks, which should affect the degree to which respondents will be patient for a financial return.

Finally, we include one instrument for the discount rate model that is a natural result of the survey method. In particular, we need a variable that is related to the revealed discount rate, but is unrelated to willingness to pay. For that, we use the difference between the first interest rate offered the respondent and the second discount rate offered. Note, that since both rates are generated randomly, the difference itself is a largely random variable.[4] Consequently, as it is randomly constructed for the discount questions only, it must be unrelated to the process which elicits WTP, below. So, it's exclusion from the WTP model is theoretically motivated. But, given that research strongly suggests that framing may be a problem in CV questions (Reaves, Kramer, and Holmes, 1999), the difference in offer rates should be a significant predictor of the imputed discount rate. Consequently, this variable, *drate2*, will be included as a predictor in the discount rate model, but excluded from the WTP model.

Table 1 presents descriptive statistics of these variables.

c. Willingness to Pay Model

c.1 – Maximum Likelihood Estimator

As with the discount rate model, we assume that each person possesses preferences for cancer screening, which is defined as a latent variable:

$$P_i^* = Z_i\beta + \eta_i$$

where $\eta_i \sim N(0, 1)$. Like the case of the discounting model, we will also restrict willingness to pay for a screen to the non-negative range. Again, a respondent is asked whether she would be willing to pay a random dollar amount P_1 for the hypothetical screening test. If the respondent's true WTP, P^*, lies above P_1 then the person would

[4] One deviation from pure randomness is that we are only able to measure a difference in rates for those respondents who answered "No" to the first question, and so were offered a higher rate in the second round question. This is because of the difficulty noted above with regard to the performance of the empirical models which incorporated the depreciating arm of the questions. However, this is not a problem from an IV perspective, as it only enhances the correlation with the underlying latent variable of interest, R^*.

answer “Yes” – at which point the question is repeated with a new (randomly assigned) higher dollar amount, P^2. If the true WTP lies below P_1 then the person would respond “No” – at which point they would be asked the question again with a new (randomly assigned) lower dollar amount, P_3.

Consequently, for a person to respond “Yes – Yes” (designated YY), it must be true that $P^*_i > P_2$. The probability of this occurring is:

$$Pr[YY] = Pr[P^* = Z_i\beta + \eta^i > P_2]$$

$$= Pr[\eta_i < Z_i\beta - P_2]$$

so,

[Eq. 5] $$Pr[YY] = \Phi(Z_i\beta - P_2)$$

Again, $\Phi(.)$ represents the standard normal CDF, Z_i is a set of explanatory variables, and β is a vector of parameters to be recovered from the maximum likelihood estimation. Equation 5 represents the probability that η_i falls into region IV in Figure 2.

Similarly, when a person responds “Yes – No” (designated YN), it must be true that $P_1 < P^*_i < P_2$. The probability of this occurrence is:

$$Pr[YN] = Pr[P_1 < Z_i\beta + \eta_i < P_2]$$
$$= Pr[P_1 - Z_i\beta < \eta_i < P_2 - Z_i\beta]$$

so,

[Eq. 6] $$Pr[YN] = \Phi(P_2 - Z_i\beta) - \Phi(P_1 - Z_i\beta)$$

Equation 6 represents the probability that η_i falls into region III in Figure 2.

Applying the same reasoning, one can demonstrate that the probabilities that the respondent's latent WTP lies within regions II and I in Figure 2 (respectively) are:

[Eq. 7] $\Pr[NY] = \Phi(P_1 - Z_i\beta) - \Phi(P_3 - Z_i\beta)$

[Eq. 8] $\Pr[NN] = \Phi(P_3 - Z_i\beta) - \Phi(- Z_i\beta)$

Recall, as with the discount rate model, we bound admissible WTP above 0, which implies that η_i must lie strictly above $- Z_i\beta$.

As above, if we define dummy variables, d^{YY}, d^{YN}, d^{NY} and d^{NN} to indicate when each of the respective outcomes obtain, then the log likelihood function becomes:

[Eq. 9] $\ln L = d^{YY} * \ln\{\Phi(Z_i\beta - P_2)\} + d^{YN}*\ln\{ \Phi(P_2 - Z_i\beta) - \Phi(P_1 - Z_i\beta) \} +$

$d^{NY}*\ln\{ \Phi(P_1 - Z_i\beta) - \Phi(P_3 - Z_i\beta) \} + d^{NN}*\ln\{ \Phi(\Phi(P_3 - Z_i\beta) - \Phi(- Z_i\beta) \}$

which is maximized across β. In actual implementation, the maximum likelihood estimator requires parameters on the offer prices (which are effectively identical), just as in the case with the discount rate model. Again, the true parameters of interest are $\hat{\beta} = \frac{\hat{\beta}_1}{\hat{\alpha}}$, where $\hat{\beta}_1$ are the parameters generated by the maximum likelihood estimator on Z, and $\hat{\alpha}$ is the average parameter on the offer prices. We report $\hat{\beta}$ in the tables below. Once we have recovered the normalized parameter vector $\hat{\beta}$, then we can estimate a WTP for each individual, *i*, in the data, $\hat{P}_i^* = Z_i\hat{\beta}$.

c.2 – Explanatory Variables:

We include explanatory variables that fall into several classes. These are:

- *characteristics of the individual that are expected to influence general preferences* – respondent age (*age*), gender (*male*), race (*black* and *otherrace*), marital status (*married*), and educational attainment (*hschool*, and *somecoll*).
- *characteristics that reveal underlying preferences with respect to value of cancer screen* – self-reported health status (*goodhealth*), self-reported cancer risk (*selfcnrisk*), and smoking status (*formersmoker*).
- *characteristics that affect the opportunity costs of medical care* – insurance status (*medicare*, *Medicaid*, *selfins*, *hmo*, and *otherins*), employment status (*employed*, and *retired*), and income (*inc1 – inc6*, and *unknowninc*).

Definitions of these variables can be found in the discussion on the explanatory variables for the discount rate model above.

Finally, we include one instrument for the willingness to pay model similar to the instrument on the discount rate model. Again, it is a natural result of the survey method - the difference between the first offer price for the cancer screen and the second offer price. Again, since both prices are generated randomly, the difference itself is a random variable. Consequently, as it is randomly constructed for the willingness to pay questions only, it should be unrelated to the process which elicits discount rates above. Again, given the potential for framing, we expect the difference in offer prices, dprice, to influence the imputed WTP.

Table 1 presents descriptive statistics of these variables.

IV. Results

Table 2 presents the maximum likelihood estimates of $\hat{\theta}$ -which are normalized by the parameter on the offer rates. While this model is of principle interest insofar as it is used to generate an imputed interest rate for each individual, several results are of interest. The first is that the instrument drate2 is highly significant (as expected), though the regional and year dummy variables are not. Given that the market rates on certificates of deposit and savings accounts usually exhibit significant regional and temporal variation, it is surprising that these opportunity costs of adopting the hypothetical delayed payments did not seem to influence observed individual discount rates. However, it should be noted that the period in which the survey was administered (second half of 2002 and first half of 2003) correspond to a period of nearly record lows in short term interest rates since World War II. Consequently, as the rates being offered in the survey were generally an order of magnitude higher (mean of 20% compared 2%) than the market rates, any small geographical or temporal variation may have been economically meaningless.

Several of the other results are of some interest. Older respondents had higher rates of discount than younger respondents – at approximately one-half percentage point per year (significant at better than the 1% level). That older individuals would be less patient is consistent with findings in the literature (Frederick, Loewenstein, and O'Donoghue, 2002), and is often explained as a risk effect: older individuals may perceive the likelihood that they will be alive in six years to collect the award to be lower, and therefore less patience with respect to the timing of the reward. Additionally, we find that individuals with lower incomes have higher rates of discount than individuals with higher incomes. Individuals in the lowest three income levels (corresponding to $0 to $19,999, $20,000 to $29,999 and $30,000 to $39,999 respectively) have about a 15% higher annual discount rate than individuals with incomes in excess of $100,000. These are generally significant at the 5% level or better - except for the parameter on the indicator variable for income between $20,000 and $29,999, which is only marginally significant. Again, this is consistent with expectations since individuals with lower incomes will face higher opportunity costs for delaying the rewards, and so behave in a manner consistent with higher rates of discount. Additionally, people who are less patient in general will tend to invest less heavily in income-generating human capital (which typically requires delaying gratification), and so tend to have lower incomes. In this sense, income may proxy for an unobservable characteristic of the respondent related to the willingness to delay gratification.

One result was not expected, and that is the parameter values associated with schooling. Since we are surveying only respondents aged 40 or higher, schooling is predetermined (in all but fringe cases). However, one would generally expect that higher levels of schooling would be associated with more patient individuals (who should have lower rates of discount). Further, one might expect schooling to train people to be more patient, on average. However, we find that respondents with lower levels of schooling have lower discount rates than individuals with more schooling. High school graduates have implied discount rates that are 16.1% lower than college graduates, and respondents with only some college have discount rates 15.6% lower than college graduates (both significant at better than the 1% level). This implies that the imputed discount rates for high school graduates and those with some college education are approximately half as large as the imputed discount rates for college graduates – a large effect.

Finally, once the parameter vector $\hat{\theta}$ is in hand, we can estimate an implied annual discount rate for each respondent, as $\hat{R}_i^* = X_i\hat{\theta}$. This yields an average imputed discount rate of 36.8%, which follows solidly in the mid-range of previously estimated discount rates using the CV elicitation method. Figure 3 presents the distribution of estimated rates, which range from -7.5% to 184.4%. Of the 1904 valid observations, 47 resulted in negative discount values (even though the likelihood function was, in principle, bounded away from parameter values resulting in negative discount rates). The WTP models were estimated both including and excluding these observations, without meaningful differences. Consequently, the negative valued discount rates are included as estimated in the second stage.

The imputed discount rate, *discount*, is included as a regressor in the WTP estimation for Equation 9 above. Since discount is an imputed variable, the standard errors generated from the standard maximum likelihood method will be biased. Consequently, the standard errors on the parameters are bootstrapped (1000 samples). Table 3 presents the marginal effects, bootstrapped standard errors on the parameters, and significance tests. After recovering the parameters in Table 3, willingness to pay for the cancer screen is calculated as $\hat{P}_i^* = Z_i\hat{\beta}$, just as in the case of the discount rate. This results in a mean willingness to pay of $282.56 – which is the amount the responses imply individuals in the sample would be willing to pay out of pocket for access to the high speed, high resolution CT screen for lung cancer. The distribution of the imputed WTP is presented in Figure 4.

The primary result of interest is the marginal effect on *discount*. The imputed discount rate has a significant (at the 6% level) negative effect on willingness to pay. Every 1% increase in the imputed discount rate reduces willingness to pay for the cancer screen by just over $5.00 (note, that a 1% chance in the imputed discount rate is equivalent to a change of 0.01 in the discount variable). To illustrate the magnitude of the discount effect, we calculated the mean imputed WTP for observations by discount rate categories (0% to 10%, 10% to 20%, etc.). These mean values are presented in Table 3. Moving from the mean cell (imputed discount rate between 30% to 40%) to the next lower cell (imputed discount rate from 20% to 30%) increases average imputed WTP from $266 to $279.

Other results are of interest as well. Men have an average willingness to pay that is $69 lower than women (significant at better than the 1% level). Non-African American minorities have a willingness to pay for cancer screening that is just over $100 lower than Caucasians (significant at better than the 1% level). Respondents who are married have a $25 higher willingness to pay for screening (significant at the 8% level). Finally, respondents who are covered by an HMO (where out of pocket costs are generally the lowest of all insurance options save Medicaid) have a willingness to pay that is $43 higher than respondents who are uninsured.

One set of results that is interesting for their lack of significance are the parameter estimates on the cancer-related variables. One would expect former smokers and those who have a self-perceived high risk cancer to have a higher willingness to pay for the screen, since the potential benefit to that group should be higher.[5] However, neither factor turns out to be a significant predictor of WTP.

[5] Both groups should have a higher objective risk of lung cancer, and so would be more likely to have a cancer actually detected by the screen. To the extent that early detection of cancer translates into better outcomes, these groups should have strictly higher benefits attached to the screen than other groups.

V. Conclusions

Preventative health care is often cited as one solution to the aging population and the growing share of health in U.S. GDP. To the extent that individuals can be persuaded to consume efficacious preventative services today, then their need for acute services in the future should be reduced. However, one significant barrier to patient adoption of preventative regimens is the fact that they generally require the person to forego consumption and activities (or lack thereof!) that they enjoy today for the promise of some future payoff. The degree to which a person prefers the present relative to the future will therefore be an important determinant in the decision calculus with respect to the demand for preventative medicine. Despite this relatively obvious observation, there have been no attempts in the literature to assess how individuals' time preferences affect the demand for preventative service.

This paper addresses this gap in the literature by analyzing data collected in a nation-wide survey of adults over the age of 40. In this survey, we used a sequential contingent valuation method to elicit responses to questions designed to reveal individual's rate of time preference and underlying willingness to pay (out of pocket) for a hypothetical cancer screen. To improve the efficiency over typical dichotomous (probit or logit) valuation models, we employed a one and one-half bounded dichotomous choice estimator to model the latent discount rate, and a double-bounded dichotomous choice estimator to model the latent willingness to pay for screening.

The results suggest that the average respondent in the survey has an underlying discount rate of 36.8%. This imputed discount rate was used as a regressor in the WTP estimation. Results indicate that higher rates of discount are associated with lower WTP for cancer screening as expected. Moving from an implicit discount rate in the mid-30% range to around 5% would result in an increase in willingness to pay from $266 to $338. However, on average, respondents to the survey reveal that they would be willing to pay around $280 out of pocket for the hypothetical cancer screening.

This research has significant implications for clinical care and for policy making. First, if the estimated discount rates are accurate, there is little hope that patients will voluntarily undertake preventative activities which entail positive costs if the benefits are much more than 5 years in the future. Beyond that point, even very large benefits to the individual will be discounted to near zero in present value terms. Consequently, clinical attempts to alter patients' behavior which stress the health benefits accruing 10, 15, or 20 years in the future (as in the case of much cardiovascular prevention) would seem doomed to failure.

Additionally, for policy makers, such high rates of discount, and clearly measured negative effects on the demand for at least some forms of prevention (in this case, cancer screening), imply that increased advocacy and education for prevention will likely not be effective tools at reducing future burdens on the health care sector. Further, from a public welfare perspective, individuals seem to reveal that they discount the future much more heavily than the market interest rate. Consequently, attempts to implement policies that promote prevention may not be Pareto improvements – in that they are inconsistent with revealed preferences. A more appropriate allocation of resources may be to increase research into acute care. High rates of discount are consistent with preferences toward current consumption of health capital and expectations that any future acute episodes will be treated when they arise, rather than prevented.

Of course, much research remains to be conducted. It remains to be seen if the demand for other types of preventative services are inversely related to individuals' discount rates – or whether acute care demand is also related to discounting. Much research into individual discounting of the future has focused on potential time-inconsistencies. These issues must also be resolved before the welfare implications of any negative discount / preventative care demand relationship is understood. Finally, while this research did indicate a significant relationship between an individual's rate of discount for financial instruments (sweepstakes prizes) and health care demand, if people discount health care itself at a different rate than they discount money, these results may not be borne out. Nonetheless, the current results do cast significant doubt on the possibility of widespread adoption of costly preventative care regimens.

Figure 1

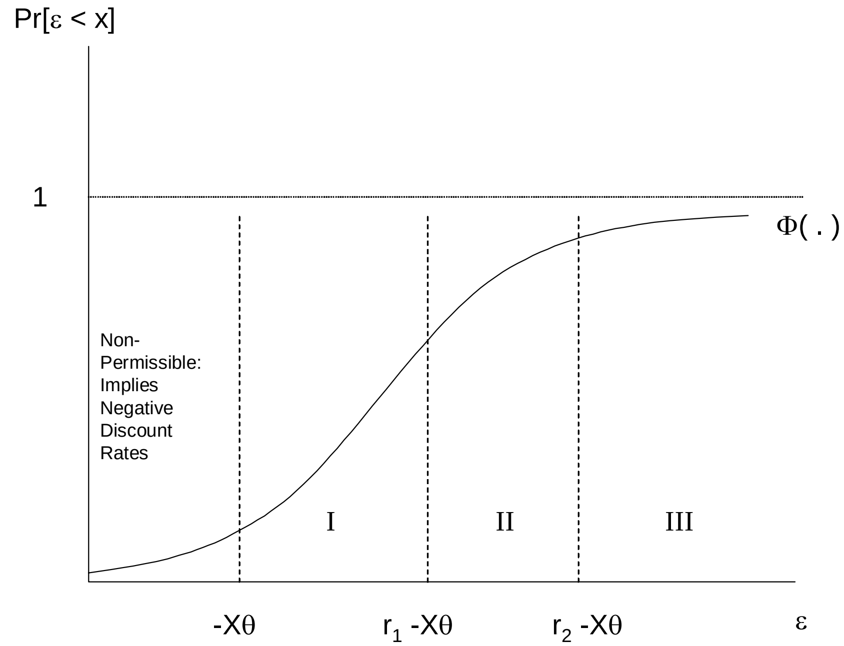


Figure 2

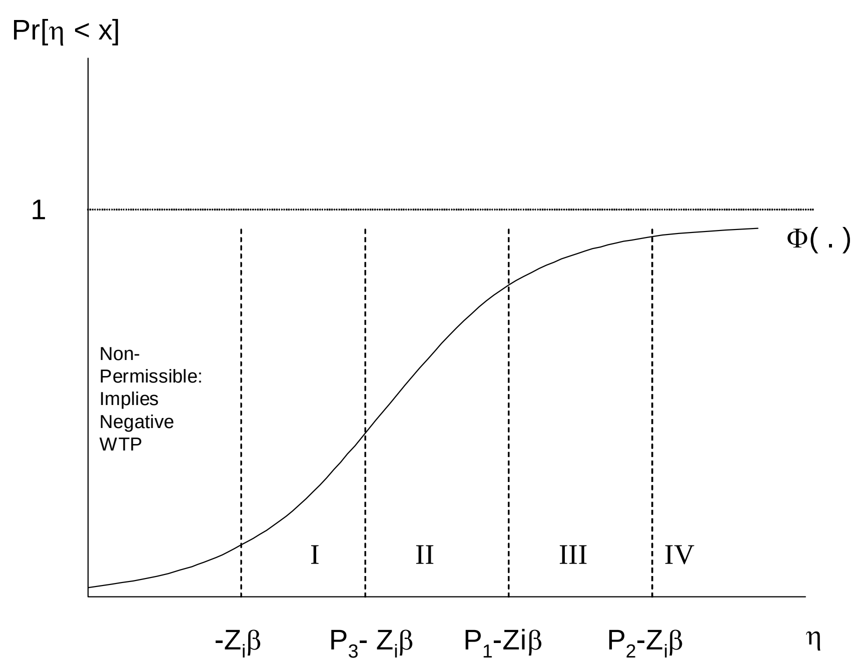
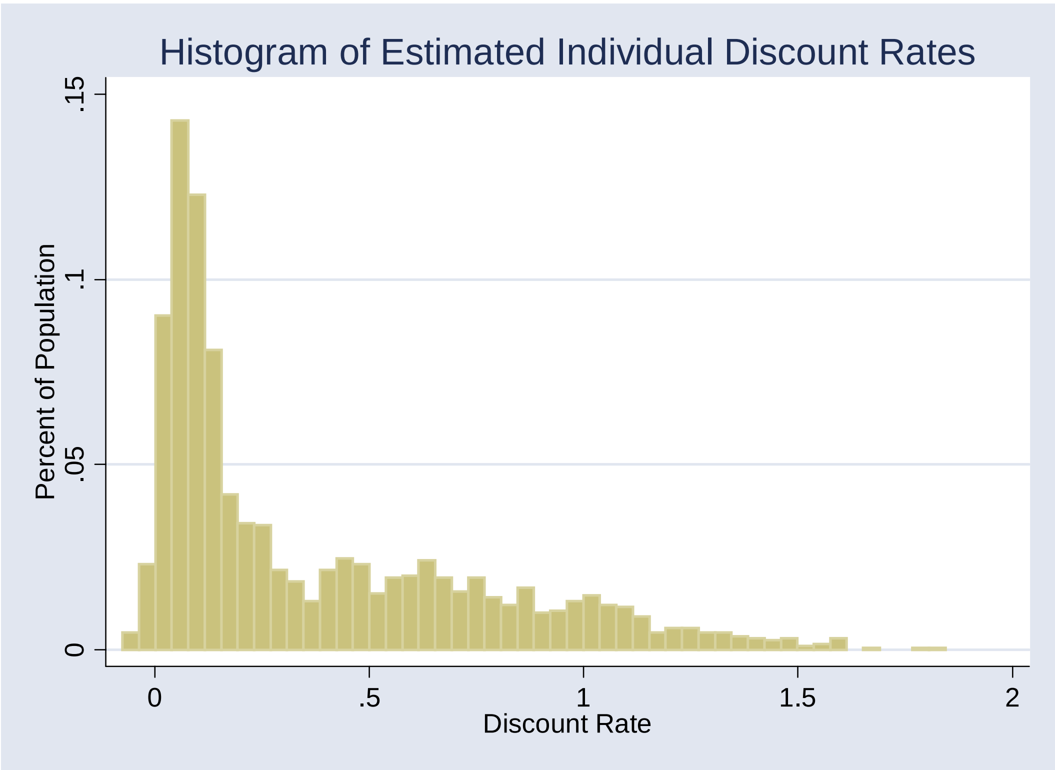


Table 2
Latent Discount Rate Model
Estimated One and One-Half Bounded Parameters

Variable		Marginal Effects	Standard Errors (on parameters)	t-statistic	p-value
drate2		-2.765	0.403	-14.67	0.000
age		0.005	0.003	3.02	0.002
male		-0.026	0.059	-0.93	0.354
goodhealth		-0.061	0.098	-1.33	0.184
formersmoke		-0.004	0.062	-0.13	0.898
selfcnrisk		-0.031	0.098	-0.68	0.496
black		-0.007	0.073	-0.22	0.828
otherrace		0.009	0.096	0.20	0.844
married		-0.013	0.061	-0.46	0.648
hschool		-0.161	0.118	-2.93	0.003
somecoll		-0.156	0.119	-2.79	0.005
medicare		0.096	0.120	1.71	0.087
medicaid		-0.033	0.173	-0.41	0.681
selfins		-0.054	0.117	-0.99	0.321
otherins		0.021	0.156	0.28	0.776
hmo		-0.043	0.061	-1.51	0.131
employed		-0.011	0.091	-0.25	0.801
retired		0.071	0.120	1.26	0.209
inc1		0.164	0.180	1.95	0.051
inc2		0.139	0.185	1.61	0.107
inc3		0.172	0.172	2.14	0.032
inc4		0.083	0.149	1.19	0.233
inc5		0.064	0.149	0.92	0.360
inc6		0.073	0.156	1.00	0.319
unknowninc		0.053	0.136	0.83	0.407
year03		0.001	0.088	0.03	0.973
newengl		0.011	0.134	0.18	0.859
southeast		0.027	0.074	0.76	0.446
midwest		-0.017	0.079	-0.46	0.644
plains		-0.003	0.140	-0.04	0.966
west		0.038	0.087	0.93	0.354
Intercept		0.049	0.274	0.38	0.702
Number of observations = 1904					
Wald Chi-Square= 397.82					
P-value on Wald Test < 0.0001					

Note: Marginal effects are coefficients normalized by the parameter on the second offer rate

Figure 3



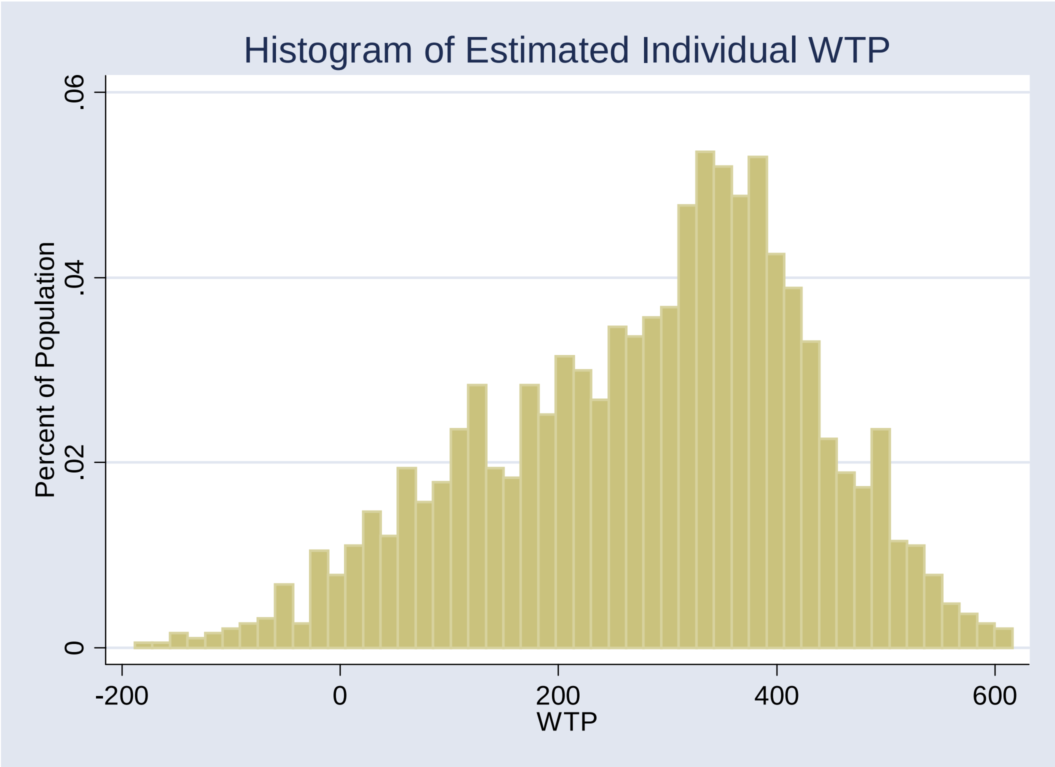
Histogram of Estimated Individual Discount Rates
Percent of Population
0
.05
.1
.15
0
.5
1
1.5
2
Discount Rate

Table 3 Latent Willingness to Pay Model Estimated Double Bounded Parameters					
Variable		**Marginal Effects**	**Standard Errors (on parameters)**	**t-statistic**	**p-value**
discount		-51.377	0.175	-1.88	0.060
dprice		-0.974	0.001	-4.28	0.000
age		-0.892	0.006	-1.02	0.306
male		-69.105	0.129	-3.44	0.001
goodhealth		12.191	0.129	0.61	0.545
formersmoke		25.560	0.104	1.57	0.116
selfcnrisk		-16.577	0.138	-0.77	0.442
black		-12.466	0.117	-0.68	0.496
otherrace		-103.728	0.196	-3.38	0.001
married		26.255	0.096	1.76	0.079
hschool		9.834	0.143	0.44	0.661
somecoll		42.278	0.159	1.70	0.089
medicare		-18.107	0.171	-0.68	0.498
medicaid		-38.768	0.268	-0.92	0.355
selfins		5.546	0.188	0.19	0.850
otherins		-6.535	0.239	-0.17	0.861
hmo		42.825	0.110	2.49	0.013
employed		15.345	0.144	0.68	0.496
retired		25.828	0.190	0.87	0.383
inc1		-42.146	0.292	-0.92	0.356
inc2		-1.053	0.279	-0.02	0.981
inc3		-0.699	0.277	-0.02	0.987
inc4		8.477	0.257	0.21	0.833
inc5		-50.406	0.263	-1.23	0.220
inc6		-19.880	0.283	-0.45	0.653
unknowninc		-34.130	0.242	-0.90	0.367
intercept		318.238	0.218	9.36	0.000
Number of observations = 1904					
Wald Chi-Square= 763.87					
P-value on Wald Test < 0.0001					

Note: Marginal effects are coefficients normalized by the parameter on the offer prices

Table 4 Changes in Estimated WTP for Observations with Varying Estimated Discounts				
Value of Imputed Discount Rate	**Number of Observations in Cell**	**Mean Estimated WTP in Cell**	**Minimum Estimated WTP in Cell**	**Maximum Estimated WTP in Cell**
0%<=discount<10%	586	$338	-$51	$610
10%<=discount<20%	345	$309	-$165	$611
20%<=discount<30%	147	$279	-$71	$568
30%<=discount<40%	87	$266	-$123	$536
40%<=discount<50%	115	$267	-$102	$616
50%<=discount<60%	94	$233	-$128	$501
60%<=discount<70%	96	$224	-$58	$529
70%<=discount<80%	70	$202	-$188	$498
80%<=discount<90%	70	$202	-$188	$498
90%<=discount<100%	54	$169	-$156	$499

Figure 4



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